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Machine-Learning-Based Classification of Urban Voids: Case Study of "Balat and Fener, Istanbul, Turkey"

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Abstract

Climate change is one of the most significant challenges humanity is facing today. As major contributors to greenhouse gas emissions, cities have a crucial role in mitigating its effects. One resource that cities can leverage in this fight is their Urban Voids (UVs) - undermanaged spaces that, when adequately repurposed, can provide a range of benefits, such as supporting urban biological ecosystems and helping to address climate change. This study proposes a machine-learning-based classification of UVs in "Balat" and "Fener" in Istanbul, Turkey. By classifying UVs based on their ability to assist ecological restoration and community growth, this study offers a valuable tool for urban planners and policymakers to prioritise their efforts and spend resources more efficiently in the fight against climate change. The classification in this study is based on five factors - Ownership, Debris, Economic activity, Seal, and Leisure facilities - which were selected based on their significance in previous studies of UVs. A decision tree algorithm was employed to classify the UVs into six categories, and an artificial neural network (ANN) was used to validate the classification with an accuracy of 97%. Overall, this study offers insights into the potential of machine learning in UV classification and provides a valuable tool for urban planners and policymakers to manage and activate UVs effectively.

Keywords: urban voids, interim reuse, decision tree, machine learning, climate change mitigation

1. Introduction

Cities are the primary habitat for humanity, and according to the United Nations declarations, they continue to attract more populations (United Nations et al., 2019). As populated urban areas continue to expand rapidly, it often leaves undermanaged, undesired, and impractical spaces behind that are odd in shape and ambiguous in function. These undermanaged spaces have received many names after Trancik highlighted their importance for cities in 1986 (Trancik, 1986). According to Trancik (1986), "Lost Spaces" are places that are "in need of re-design, anti-spaces, making no positive contribution to the surroundings or the users." Other scholars who studied these particular spaces annexed names such as loose, liminal, vacant, in-between, transitional, indeterminate, accessible, and neglected (De Girolamo, 2013). This study will regard these spaces as "Urban voids" or UVs despite the existence of many names to address them. UVs are often

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seen as negative spaces that could be better utilised (Bowman, 2004; Branas et al., 2018; Goldstein et al., 2001; Kim et al., 2018; Lopez-Pineiro, 2020; Mhatre, 2007; US EPA, 2022). However, when repurposed, UVs can provide benefits such as supporting urban ecosystems and addressing climate change (Kelleher et al., 2020; Kim et al., 2015; Németh & Langhorst, 2014). They can be used for community gardens, urban agriculture, and commercial ventures. Ecologically, they can improve stormwater infiltration, air quality, and soil contamination. UVs can also help reduce a city's carbon footprint through initiatives like urban agriculture and greening projects (Branas et al., 2018; Kelleher et al., 2020).

Cities may construct more resilient and sustainable communities by incorporating UVs into their climate change adaptation strategies. Classifying UVs is a key step in efficiently managing and engaging these places. By analysing essential features such as Ownership, Debris, Economic activity, Seal, and Recreational facilities, urban planners and policymakers may better grasp the potential of these areas for promoting sustainable urban planning and regenerative design. With the advances made in computer sciences, many researchers try to incorporate Machine-Learning or ML-based approaches, such as ML-based subject detections or ML-based classifications, into their research. They can be useful for evaluating massive datasets and detecting patterns influencing decision-making. Cities may prioritise their efforts and spend resources more efficiently by categorising UVs based on their ability to assist ecological restoration and community growth.

2. Literature Review

Many academics and researchers have assigned different classifications to UVs depending on their research emphasis and the particular setting they are examining. For instance, some studies concentrate on the origin and the reason for UVs' creation, while others might focus on where they are or how they might be used again. Although there is a manifold of classifications, the reason for having more than one classification is also valid and rational. Researchers and academics frequently create their classifications and frameworks to examine the phenomena they are investigating uniquely. Also, it helps them to have a better comprehension of their study subjects. They may even get fresh perspectives as a result and contribute to the current academic conversation on their subject (Bhaskaran, 2018; Carmona, 2010; De Girolamo, 2013; Hashem et al., 2022; Hwang & Lee, 2020; Kim et al., 2018; Lee & Newman, 2019; Lopez-Pineiro, 2020; Németh & Langhorst, 2014).

As discussed before, numerous terminologies address urban spaces that require attention or are left unused and undermanaged. Due to the existence of various terminology for these spaces, the attempts to classify these spaces are also manifold (Rupprecht & Byrne, 2014; Sanches & Mesquita Pellegrino, 2016; Xu & Ehlers, 2022). For instance, Nemeth and Langhorst adopted a classification of vacant land from Northam (1971), which categorised them into three distinctive classifications. The first one is Remnant Parcels. This type of vacant land is small in size and irregular in shape; they occur on high slopes with the dangers of flooding or in protected view planes with geographical or regulatory limitations. These all have the characteristic of being underdeveloped in common. The second type is Reverse parcels. These are the lots held by private owners for the future expansion of lands in gentrifying areas. Alternatively, they sometimes are held by public agencies for future sale development. The third type is TOADS, the abbreviation of Temporary Obsolete abandoned or derelict sites. They cover a wide range of sizes and previous uses in the sites of former industrial or commercial activities. However, there is a crucial factor: the presence or absence of contamination (Németh & Langhorst, 2014; Northam, 1971).

Machine Learning (ML), a branch of artificial intelligence, involves creating algorithms to learn from data and make predictions or decisions. These techniques have been increasingly applied in various fields, including urban planning and management (Chaturvedi & De Vries, 2021). ML-based algorithms can analyse large datasets and identify patterns to inform decision-making. Several ML techniques can be applied to classify UVs, including decision trees (DTs), random forests (RFs), artificial neural networks (ANNs), and support vector machines (SVMs) (Talukdar et al., 2020). Although some research has investigated ML-based methods concerning UVs, such as vacant land detection (Xu & Ehlers, 2022), no research has proposed a method for classifying UVs based on ML-based techniques. Hence, this paper targets the gap by providing a methodology for implementing ML in UVs classification.

3. Methodology

3.1. A Brief History of the Case Study

The Golden Horn has been essential in Istanbul's growth as a seaport, naval base, residential community, and religious centre throughout its long and rich history. It also has a wealth of past where people came to live, work, and play. The neighbourhoods of Fener and Balat, located south of the Golden Horn, were once home to Greek, Jewish, and Armenian communities. However, in the mid-20th century, these communities were replaced by Muslim immigrants from Anatolia. The area also faced challenges such as pollution and decay due to the growth of industries. In the 1980s, the local government strategically revitalised the area by transforming it into a cultural and tourist destination. They did this by bulldozing old neighbourhoods, removing industrial plants, and building new roads and green spaces. In recent years, different groups have tried to transform the area, leading to different ideas about what it should be. These efforts have sparked important conversations about shaping the city (Bezmez, 2007; Stoquart & Çağlar, 1998). Numerous projects have been carried out to conserve and improve the Golden Horn region during the 20th and 21st centuries. These attempts have included various programs, including the Golden Horn Rearrangement Project, which ran from 1984 to 1989, the Fener-Balat Rehabilitation Program from 2003 to 2007, and the Henry Proust Plan, which was in existence from 1938 to 1950 (Kishali & Rosina, 2018).

Additionally, renewal acts have been used to put contemporary urban transformation plans into effect. These different programs show the continuous dedication of regional leaders and interested parties to protecting and developing the Golden Horn region, which has been crucial to Istanbul's history and is still a major cultural and tourism attraction. Despite all these actions to help revitalise these neighbourhoods, Balat and Fener's current conditions still require immediate action. These actions' priorities must align with treating the undermanaged spaces or UVs that exist abundantly in the district.

3.2. Urban Void Identification

This research's methodology proposes an objective method for classifying each UV into a unique class. To scientifically classify UVs of the study area, having a reliable method for identifying any land parcel as UVs is crucial. The first step to identify any land as a UV, objectively and bias-free, is to define the subject of the inquiry and its essential criteria. The most logical approach is to define it with respect to the first origin of the phenomenon. As stated in section 2, Roger Trancik, a well-known figure in urban design, has made a tremendous contribution to the field. In his book "Finding Lost Space: Theories of Urban Design" (1986), Trancik investigated these spaces and referred to them as "Lost Spaces." Identifying these spaces in this research's case study requires using Trancik's theories of "Figure-ground," "Linkage," and "Place Theories." These theories offer a framework for examining an urban area's spatial organisation and locating lost places. Identifying UVs in a neighbourhood can be controversial. According to Trancik's description, several variables determine whether a space should be considered a Lost Space. These spaces are abandoned and do not benefit the environment or users. If a space satisfies these requirements, it can be considered a Lost Space. However, it would not be considered a Lost Space if it is well-maintained and provides value to the neighbourhood. It is also essential to examine the space utilising figure-ground, linkage, and place theories to decide whether a particular space would be considered a Lost Space. This study examined the case study neighbourhoods based upon Trancik's theories and identified 588 lands as UVs

3.3. A Five-Feature Decision Tree

This research classifies the mapped 588 UVs in the case study into six distinct classes: Inert, Institutional, Greensward, Residual, In-between, and Blocked. The classification is done using a five-feature decision tree. After identifying and mapping all the UVs in the study area, they received a binary value of either zero or one for the five features' existence or absence. These five features are Ownership, Debris, Economic activity, Seal, and Leisure facilities. It must be mentioned that these five features are obtained based on a thorough literature review. However, the names of these features are given by the authors.

"Ownership" in UVs can extend beyond legal possession to communal belonging, affecting potential uses and development and making publicly-held land more accessible. In contrast, privately owned land may require negotiation with the owners (Hashem et al., 2022). The physical state of a UV, including debris such as litter and garbage, can affect its suitability for various uses and potential environmental consequences. "Debris" can negatively impact the surrounding community and environment and accumulate due to insufficient maintenance and vandalism (Gardiner et al., 2013; López et al., 2021; Nassauer & Raskin, 2014). UVs have the potential for productive uses that generate "Economic Activity" that benefits the local community, such as business growth and job creation. However, challenges may arise in unlocking their potential due to weak state laws governing tax foreclosure and other areas (Hashem et al., 2022; Hwang & Lee, 2020). The "Seal" of a UV refers to its physical accessibility. Open UVs are easily accessible and can facilitate community use and development, while closed UVs may require additional effort and negotiation to utilise (Elbeah et al., 2022; Khalid et al., 2018). UVs with "leisure facilities" like parks and playgrounds may appeal to the public and serve as community gathering points. However, UVs lacking recreational amenities may be perceived as less desirable(Žlender & Gemin, 2020).

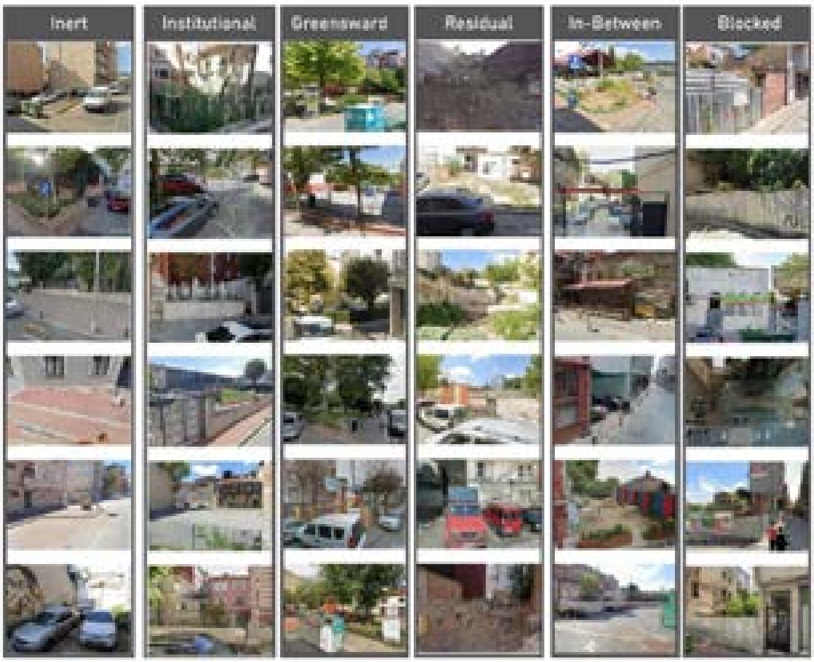

Figure 1. Examples of the Dataset and their Classes

4. Results

4.1. Decision Tree Algorithm: Six Categories of UVs

After identifying and mapping the UVs in the study area, the next step was to analyse them based on the five mentioned features. The next step was to prepare the data for their classification. In this respect, an Excel spreadsheet was made to list all the UVs as examples of the decision tree algorithm to receive their binary value (1 or 0) for each feature based on whether the trait is present or absent. The next step entailed dividing the data set into two subsets: the training and test sets, with an 80 to 20 per cent ratio. The training set included a dataset of labelled UVs with binary values for each feature used to train the model. The trained model was then applied to the test set, a dataset including unlabelled UVs.

A model's performance can be evaluated using various metrics to assess its effectiveness. These metrics include recall, which measures the proportion of accurate positive classifications among all actual positive instances; precision, which measures the proportion of actual positive classifications among all positive classifications; and accuracy, which measures the proportion of correct classifications (Fürnkranz, 2010). Figure 2 shows the decision tree result.

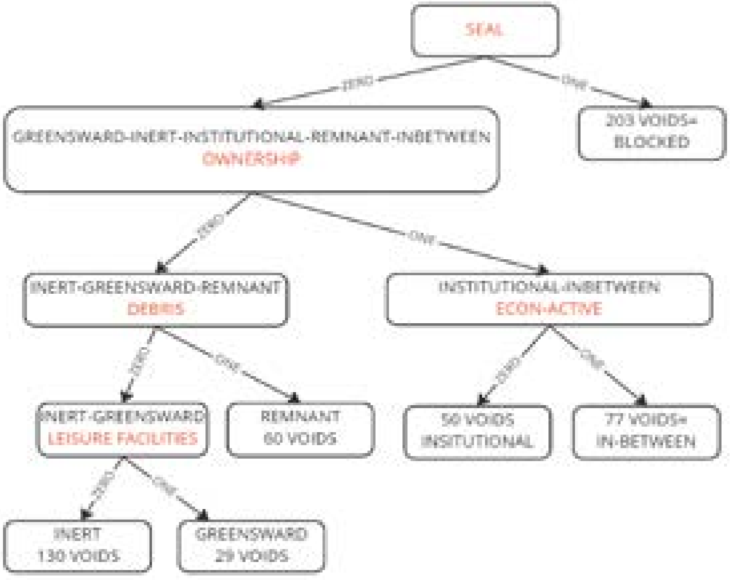

Figure 2. The Decision-Tree Algorithms' Result

4.2. Automation and Validation of Classification Using ANN

After using the decision tree method to classify UVs, the next step was to evaluate the classification's accuracy and create predictions for data that did not have labels. While decision trees can be beneficial for establishing rules to categorise new data, they can sometimes overfit the data (Alpaydin, 2004). Hence, it is essential not only to consider the model's well performance on the training data as it might not yield accurate predictions on new data. An artificial neural network (ANN) model was used to guarantee that the classification was correct and could be applied to new data. Artificial Neural Networks (ANNs) are ML models inspired by the structure and function of the human brain. These models comprise several layers of linked nodes, or neurons, that process and transfer data throughout the network.

```
[ ] preferred_model = Sequential(
        [
            Dense(10, activation = 'relu'),
            Dense(6, activation = 'linear')    #<-- Note
        ]
    )
    preferred_model.compile(
        loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
        optimizer=tf.keras.optimizers.Adam(0.001),
    )

    preferred_model.fit(
        X_train,y_train,
        epochs=200
    )
```

Figure 3. The ANNs Network Architecture

ANNs may learn complicated correlations between inputs and outputs and can be used to perform a variety of tasks such as classification, regression, and prediction (Casas, 2020; Jain et al., 1996). Hence, this research used TensorFlow, a well-known open-source library for developing and training ML models such as ANNs. The initial step in developing an ANN model with TensorFlow is to specify the network's architecture, which includes defining the number and size of network layers and the activation and loss functions used for training the model (Sarang, 2021). After creating the network's architecture, the model is trained on a labelled dataset. This step requires employing an optimiser to change the weights and biases of the network's neurons to minimise the loss function. The model is trained until it achieves a desirable degree of accuracy on the training data. The final step evaluates the trained model's performance on a separate validation dataset. Which assesses the model based on accuracy and generalizability and how well it will perform on new data.

```
p_preferred = preferred_model.predict(X_test)
print(f"two example output vectors:\n {p_preferred[:2]}")
print("largest value", np.max(p_preferred), "smallest value", np.min(p_preferred))
```

```
6/6 [==============================] - 0s 2ms/step
two example output vectors:
 [[-0.44082713 -3.166368   -3.8406265   2.580936   -5.1028657  -4.7933874 ]
 [-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ]]
largest value 5.797967 smallest value -5.1028657
```

```
for i in range(10):
    print( f"{p_preferred[i]}, category: {np.argmax(p_preferred[i])}")
```

```
[-0.44082713 -3.166368   -3.8406265   2.580936   -5.1028657  -4.7933874 ], category: 3
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
[ 3.8226926 -2.1985672 -3.3256078 -2.8819475 -3.670209  -2.7123098], category: 0
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
[ 3.8226926 -2.1985672 -3.3256078 -2.8819475 -3.670209  -2.7123098], category: 0
[-1.444407   1.1016548 -4.0788155 -4.6486125  5.3980474 -4.7311935], category: 4
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
[-1.0171394   0.08716151 -4.391338   -3.1762376  -4.1569266   5.797967  ], category: 5
```

```
print (y_test[:10])
```

```
[3 5 0 5 5 0 4 5 5 5]
```

Figure 4. Testing the Model for Prediction

5. Conclusion

In conclusion, this study demonstrates the potential of ML in classifying UVs based on their ability to assist ecological restoration and community growth. By employing a decision tree algorithm and validating the classification with an artificial neural network (ANN) with an accuracy of 97%, this study offers a valuable tool for urban planners and policymakers to prioritise their efforts and spend resources more efficiently in the fight against climate change. The classification of UVs in Balat and Fener in Istanbul, Turkey, based on five factors - Ownership, Debris, Economic activity, Seal, and Leisure facilities - provides insights into the characteristics that are most significant in determining the potential of UVs to support urban biological ecosystems and address climate change. These findings can inform the development of effective strategies for managing and activating UVs. Overall, this study contributes to the growing body of research on the potential of ML-based approaches in urban planning and offers a practical tool for managing and activating UVs in cities. Further research could explore the application of this approach in other cities and contexts to assess its generalizability and potential for broader adoption.

Conflict of Interests

The author declares no potential conflict of interest was reported by the author.

Endnotes

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